Journal of Science and Technology
ISSN: 2456-5660 Volume 6, Issue 06 (Nov- December 2021)
www.jst.org.in *DOI:https://doi.org/10.46243/jst.2021.v6.i06.pp174 - 179*

Image Segmentation using Extended Edge Operatorfor Mammographic Images

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To Cite this Article
K Naresh Kumar, G L N V Kartheek, G V S Ch S L V Prasad, **Image Segmentation using Extended Edge Operatorfor Mammographic Images "** *Journal of Science and Technology, Vol. 0,6 Issue 06,Nov - December 2021, pp174-179*
Article Info
Received: 09-10-2021 Revised: 10-11-2021 Accepted: 10-12-2021 Published: 27-12-2021

Abstract— Detection of edges in an image is a very important step towards understanding image features. Since edges often occur at image locations representing object boundaries, edge detection is extensively used in image segmentation when images are divided into areas corresponding to different objects. This can be used specifically for enhancing the tumor area in mammographic images. In this paper extended Sobel , Prewitt and Kirsch edge operators are proposed for image segmentation of mammographic images. Edges and tumor location can be seen clearly by using this method. For comparison purpose Gray level co-occurrence matrix, watershed algorithm, present Sobel, Prewitt and Kirsch edge operators are used and their results are displayed.

Keywords- mammographic images,segmentation,edge operator

INTRODUCTION

Diagnostic imaging is an invaluable tool in medicine today. These imaging modalities provide an effective means for noninvasive mapping of the anatomy of a subject. These technologies have greatly increased knowledge of normal and diseased anatomy for medical research and are a critical component in diagnosis and treatment planning. With the increasing size and number of medical images, the use ofcomputers in facilitating their processing and analysis has become necessary. Estimation of the volume of the wholeorgan, parts of the organ and/or objects within an organ i.e. tumors is clinically important in the analysis of medical image. The relative change in size, shape and the spatial relationships between anatomical structures obtained from intensity distributions provide important information in clinical diagnosis for monitoring disease progression. Therefore, radiologists are particularly interested to observe the size, shape and texture of the organs and/or parts of the organ. For this, organ and tissue morphometry performed in every radiological imaging centre. These routine assessments are commonly subjective and quantitative, and reports typically refer to lesions as large, small, and prominent. The clinical reports usually offer morphometric data in terms of change relative to a prior study. The recognition, labeling and the quantitative measurement of specific objects and structures are involved in the analysis of medical images. Therefore, to provide the information about an object clinically in terms of its size and shape, image segmentation and classification are important tools needed to give the desired information.

Medical images edge detection is an important work for object recognition of the human organs such as lungs and ribs, and it is an essential pre-processing step in medical image segmentation [1,2]. For mammograms manifesting masses thiscorresponds to the detection of suspicious mass regions. A number of image processing methods have been proposed to perform this task. S. M. Lai et al. [3] and W. Qian et al. [4] have proposed using modified and weighted median filtering, respectively, to enhance the digitized image prior to object identification. D. Brzakovic et al. [5] used thresholding and fuzzy pyramid linking for mass localization and classification. Other investigators have proposed using the asymmetry between the right and left breast images to determine possible mass locations. Yin ***et** al.* [6] uses both linear and nonlinear bilateral subtraction while the method by Lau ***et** al.* [7]. relieson "structural asymmetry" between the two breast images . Recently Kegelmeyer has reported promising results for detecting spiculated lesions based on local edge characteristics and Laws texture features [8-10].The above methods produced a true positive detection rate of approximately 90%.The work we have done is to propose a segmentation process which identifies on a mammogram the opaque areas, suspect or not, present in the image using vector quantization.

Segmenting a mammographic images into homogeneoustexture regions representing disparate tissue types is often a useful preprocessing step in the computer-assisted detection of breast cancer. Various segmentation techniques have been proposed based on statistically measurable features in the image [11-16].Clustering algorithms, such as k-means and ISODATA, operate in an unsupervised mode and have been applied to a wide range of classification problems.

The choice of a particular technique depends on the application, on the nature of the images available (texture, ill- defined contours, shadows), on the primitives to be extracted (contours, straight segments, regions, shapes), the amount of available user time and the required accuracy of the segmentation.The work of the edge detection decides the result of the final processed image. Conventionally, edge is detected according to some early brought forward algorithms like Sobel algorithm, Prewitt algorithm and Laplacian of Gaussian operator [17], but in theory these operators belongs to the high pass filtering, which are not suitable for noisy images.Watershed algorithm has a drawback of over-

segmenting the tumor also in different segments making it obscure for identification.

The rest of the paper is organized as follows. Section 2 describes Gray level Co-occurrence Matrix, the Watershed,
In this paper Extended edge operators are proposed instead of Sobel ,Prewitt and Kirsch 3x3 kernels. Section II describes different segmentation algorithm including proposed extended edge operators. Results for both these methods are displayed in Section III and section IV concludes the work.

ALGORITHMS FOR SEGMENTATION

It is difficult, however, to compare the effectiveness of these methods because each used a unique set of digitized mammograms and the results varied between training and testing. In this section , segmentation by Gray level co- occurrence matrix[18], basic watershed algorithm [19-24] and segmentation by extended edge operators are compared which are used for tumor detection

Gray Level Co-occurrence Matrix

Haralick [18] suggested the use of gray level co-occurrence matrices (GLCM) for definition of textural features. The values of the co-occurrence matrix elements present relative frequencies with which two neighboring pixels separated by distance *d* appear on the image, where one of them has gray level *i* and other *j*. Such matrix is symmetric and also a function of the angular relationship between two neighboring pixels. The co-occurrences matrix can be calculated on the whole image, but by calculating it in a small window which scanning the image, the co-occurrence matrix can be associated with each pixel.
By using gray level co-occurrence matrix we can extractdifferent features like probability, entropy, energy, variance, inverse moment difference etc .Some of them are defined as: Maximum Probability: $\max(P_{ij})$ (2.1) along region boundaries. The image feature space is treated, using a suitable mapping, as a topological surface where higher values indicate the presence of boundaries in the original image data. It uses analogy with water gradually filling low lying landscape basins. The size of the basins grows with increasing amounts of water until they spill into one another. Small basins (regions) gradually merge together into larger basins. Regions are formed by using local geometric structure to associate the image domain features with local extremes measurement. Watershed techniques produce a hierarchy of segmentations, thus the resulting segmentation has to be selected using either some prior knowledge or manually. These methods are well suited for different measurements fusion and they are less sensitive to user defined thresholds. We implemented watershed algorithmfor mammographic images as mentioned in [25]. Result for mammographic images are displayed in Figure 13(b).

C..Extendend Edge Operator

Generally Sobel, Prewitt and Kirsch operators(3x3 kernels) are used for edge detection purpose. To locate tumor or to segment tumor from mammographic images here extendedSobel ,Prewitt and Kirsch edge operators are proposed .These three operators are explained in detail in the preceeding section.

Sobel Operator

The Sobel operator performs a 2-D spatial gradient measurement on an image and so emphasizes regions of high spatial frequency that correspond to edges. Typically it is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. In theory at least, the operator consists of a pair of 3x3 convolution kernels as shown in Figure 1.
Variance:

the edge, from darker to brighter values.
To achieve better segmentation 3x3 kernels are modified to 5x5 kernels which show linear regions more clearly than in previous case. These 5 X 5 kernels are as shown in Figure 2
.One kernel is simply the other rotated by 90º.

The results for Sobel and Extended Sobel is displayed in figure7 and 10 respectively.

Prewitt operator

Prewitt is method of edge detection in image processing whichcalculates the maximum response of a set of convolution kernels to find the local edge orientation for each pixel. The Prewitt edge detector is an appropriate way to estimate the magnitude and orientation of an edge. Although differential gradient edge detection needs a rather time-consuming calculation to estimate the orientation from the magnitudes in the x- and y-directions, the Prewitt edge detection obtains the orientation directly from the kernel with the maximum response. The set of kernels is limited to 8 possible orientations; however experience shows that most direct orientation estimates are not

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www.jst.org.in DOI:https://doi.org/10.46243/jst.2021.v6.i06.pp174 - 179

much more accurate. On the other hand, the set of kernels needs 8 convolutions for each pixel, whereas the set of kernel in gradient method needs only 2, one kernel being sensitive to edges in the vertical direction and oneto the horizontal direction as shown in figure 3.

-1	-1	-1
0	0	0
+1	+1	+1

Gx

-1	0	+1
-1	0	+1
-1	0	+1

Gy

Figure 3: Prewitt convolution kernels (3x3)

These 5 X 5 kernels are as shown in figure 4.One kernel is simply the other rotated by 90º.

+2	+2	+2	+2	+2
+1	+1	+1	+1	+1
0	0	0	0	0
-1	-1	-1	-1	-1
-2	-2	-2	-2	-2

Gx

+2	+1	0	-1	-2
+2	+1	0	-1	-2
+2	+1	0	-1	-2
+2	+1	0	-1	-2
+2	+1	0	-1	-2

Gy

figure 4. Prewitt convolution kernels(5x5)

The results for Prewitt and Extended Prewitt is displayed in figure 8 and 11 respectively

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Kirsch edge operator

The kirsch edge detector detects edges using eight filters are applied to the image with the maximum being retained for the final image. The eight filters are a rotation of a basic compass convolution filter. For comparison with Sobel and Prewitt operator here only two directions horizontal and vertical convolution kernels (3x3) are considered as shown in Figure 5.The same steps as used for Sobel and Prewitt operators are used and results are given below.

+5	+5	+5
-3	0	-3
-3	-3	-3

Gx

+5	-3	-3
+5	0	-3
+5	-3	-3

Gy

Figure 5: Kirsch convolution kernels (3x3)

After observing these results for 3x3 kernels which are over segmented for mammographic images so to reduce this over segmentation 3x3 convolution kernels are modified to 5x5convolution kernels for 0º and 90º as shown in Figure 6.

+9	+9	+9	+9	+9
+9	+5	+5	+5	+9
-7	-3	0	-3	-7
-7	-3	-3	-3	-7
-7	-7	-7	-7	-7

Gx

+9	+9	-7	-7	-7
+9	+5	-3	-3	-7
+9	+5	0	-3	-7
+9	+5	-3	-3	-7
+9	+9	-7	-7	-7

Gy

figure 6: Kirsch convolution kernels (5x5)

The results for Kirsch and Extended Kirsch is displayed in figure 9 and 12 respectively

The results for this section for Gray level co-occurrence matrix, watershed algorithm and proposed extended edge operators are displayed in section III.

RESULTS

Mammography images from mini-mias database were used in this paper for implementation of GLCM, Watershed and Extended Edge operators for tumor demarcation. Figure 7 (a) shows original image with tumor. It has fatty tissues as background. Class of abnormality present is CIRC which means well-defined/ circumscribed masses. This image (mdb028 from database) has malignant abnormality.

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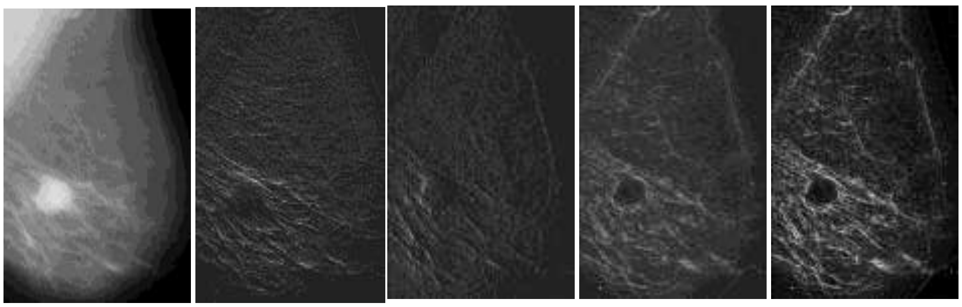
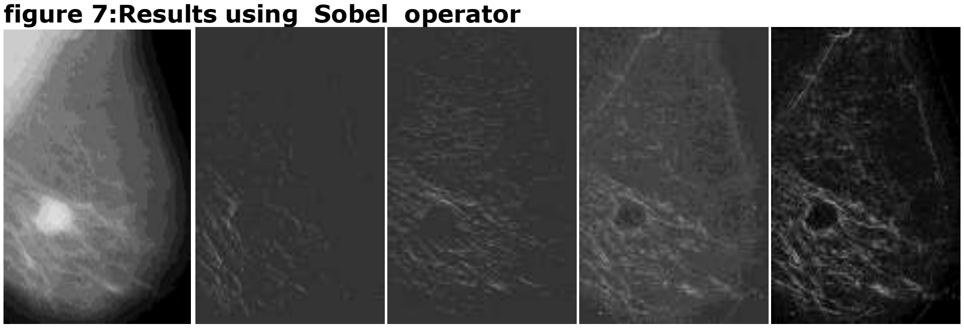
Location of the center of abnormality is (338,314) for x, y image co- ordinates. Approximate radius is 56(in pixels) of a circle enclosing the tumor.

Results for Sobel, Prewitt and Kirsch operators are shown in Figure 7-9.In these figures (a) indicates original image, Figure(b) is for horizontal edges where as figure (c) is for vertical edges. Figure (d) shows result for slope magnitude for horizontal and vertical edges. For Sobel and Prewitt edge operators , for visibility purpose slope magnitude images are scaled up since the values of that images were too small.Results for extended Sobel, Prewitt and Kirsch edge operators are shown in figure 10-12.In these cases ,scaling is not required since values are quite ok and properly visible. Figure 13(a) gives result for equalized entropy using GLCM .Figure 13(b) shows result for watershed algorithm and figure 13(c) gives result for Sobel operator whereas (d) displayed the result for extended Sobel edge operator for original image.



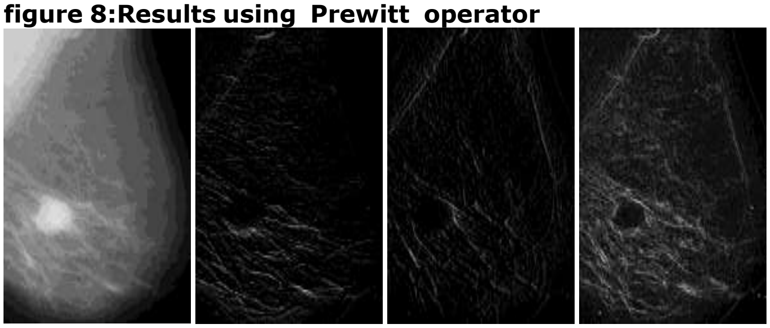
Original Image (b) Horizontal Edges (c) Vertical Edges (d) Slope Magnitude (e) Scaled Image

figure 7:Results using Sobel operator



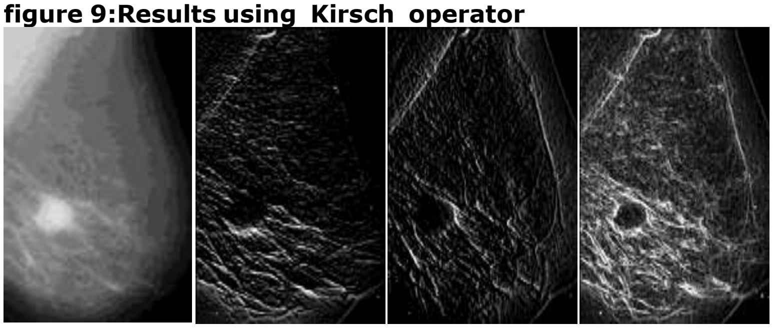
Original Image (b) Horizontal Edges (c)Vertical Edges (d)Slope Magnitude (e)Scaled Image

figure 8:Results using Prewitt operator



Original Image (b) Horizontal Edges (c) Vertical Edges (d) Slope Magnitude

figure 9:Results using Kirsch operator



Original Image (b) Horizontal Edges (c) Vertical Edges(d) Slope Magnitude

figure 10:Results using Extended Sobel operator

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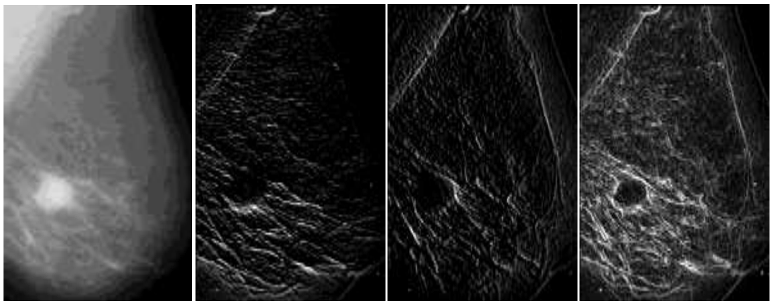
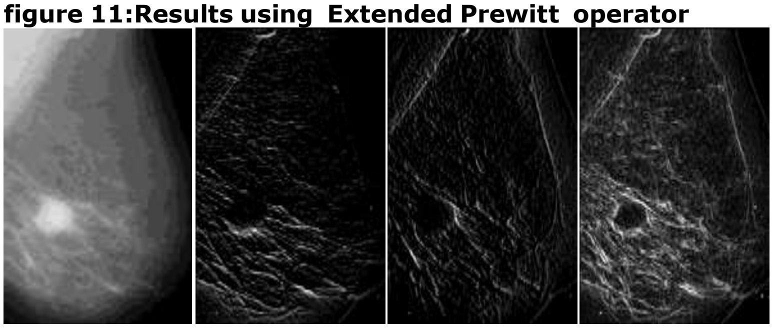


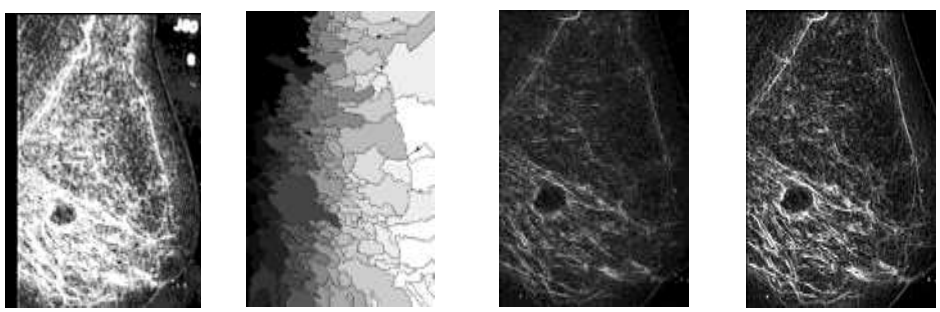
Original Image (b) Horizontal Edges (c) Vertical Edges(d) Slope Magnitude

figure 11:Results using Extended Prewitt operator



(a) Original Image (b) Horizontal Edges (c) Vertical Edges(d) Slope Magnitude

figure 12:Results using Extended Kirsch operator



(a) (b) (c) (d)

Figure 13: (a) Segmentation for equalized entropy using GLCM,(b)Segmentation using watershed algorithm,(c)Segmentation by Sobel edge operator(3x3 kernels),(d) Segmentation by Extended Sobel edge operator(5x5 kernels)

CONCLUSION

Form the results it is clear that Extended Sobel, Prewitt and Kirsch operator gives better result than Sobel, Prewitt and Kirsch operator. For 3x3 kernels the variations are highly localized hence proposed Extended edge operators which takes more neighborhood in consideration gives better result. Amongst Sobel, Prewitt and Kirsch edge operators , Sobel gives comparatively better results hence considered here for comparison.

If Extended edge operator result is compared with Gray level co-occurrence matrix , watershed and Sobel edge operator, it is observed that clear demarcation of tumor and sharp edges for the tissue can be seen in Proposed edge operator . To be more specific it is observed that for mammographic images, proposed extended 5x5 Sobel operatorgives better segmentation than Kirsch and Prewitt operator. It shows more details with proper edges which are required to observe any abnormal image which provide guidance for further treatment.

ACKNOWLEDGMENT

The authors would like to record their appreciation toDr. Manisha Munde for her help in validating the results.

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